# Evaluation of Knee Activities Using EMG Signals for Pre-predicting Lower Limb Dystonia Diseases

**Vinay Balasubramanyam [1]***       **Kalappan Balachander [1]**

[1]*Karpagam Academy of Higher Education, India*
* Corresponding author's Email: vinay.bala@gmail.com

**Abstract:** Electromyography (EMG) signal is one of the important tools for the detection of skeletal related muscular information. In this scenario, we analyse the normality and abnormality of knee movements for pre-predicting the knee dystonia diseases. It is characterized by involuntary sustained muscle contractions affecting one or more sides of the body, frequently causing twisting and repetitive movements or abnormal postures. In this paper, EMG based knee dystonia pre-prediction is assessed by employing EMG-Lower Limb dataset. Then, transformation is done by using discrete wavelet Transformation (DWT), which delivers a superior time and frequency localization ability. After transformation, hybrid feature extraction is performed by employing yule-walker, burg's, voltage level (minimum and maximum), Renyi entropy, and Peak-Magnitude to Root Mean Square Ratio (PMRS) for achieving optimal feature subsets and also to reject the redundant and irrelevant features. In most of the existing studies, an individual feature or two different features are combined for extracting the feature values from the acquired signal. In this research, five effective entropy and autoregressive features are combined to obtain more active features. After obtaining the active features, a superior binary classifier: Kernel Nearest Neighbour (KNN) is implemented for classifying the normality and abnormality of knee movements. The experimental outcome proves that the proposed methodology effectively distinguishes the normal and abnormal knee movement in terms of sensitivity, specificity, recall, precision, accuracy and E-rate. The proposed methodology improves the classification accuracy in knee movement detection upto $0.785$-$1.65\%$ compared to the existing methods.

**Keywords:** Discrete wavelet transform, Electromyography, Kernel nearest neighbour, Peak magnitude to root mean square ratio.

## 1. Introduction

Dystonia is the third most common movement disorder, yet it is still a widely under-recognized disorder, particularly to medical consultants outside of neurology [1]. This may be partly due to the variability in its clinical presentation. Dystonia movement is characterized by sustained or intermittent muscle contractions causing abnormal, often repetitive movements or postures, or both [2]. Dystonic movements are typically patterned, twisting, and may be tremulous. Dystonia is often initiated or worsened by voluntary action and associated with overflow muscle activation [3, 4]. Although, approximately 16 per 100,000 persons are affected with dystonia especially in the lower limb, dystonia is a highly visible and stigmatizing condition that adversely affects quality of life and can cause considerable morbidity [5]. In recent times, numerous lower limb dystonia detection techniques are presented that depends on the knee movement using EMG signal [6, 7]. In these existing techniques, the effectiveness of normality and abnormality classification of knee movement for pre-predicting the knee dystonia diseases is poor; due to more artifacts in the acquired EMG signal [8 - 10].

In this paper, an efficient technique is utilized to inspect the EMG signal. At first, the EMG signals are acquired from the dataset: EMG-Lower Limb database. The unwanted artifacts in the acquired EMG signals are eliminated by employing normalization and windowing techniques. After pre-processing the EMG signal, an effective

transformation methodology named as DWT is employed, which helps to reveal the local characteristics and also to reduce the feature degradation. **Proposed:** Then, hybrid feature extraction (yule-walker approach, burg's method, voltage level (minimum and maximum), Renyi entropy, and PMRS) is applied on DWT sub-bands for extracting the active feature values. Hybrid feature extraction is the procedure of obtaining optimal feature subsets from the set of data inputs by the rejection of redundant and irrelevant features. Output of the hybrid feature extraction process specifies, which features of the EMG signals are essential in describing the dataset signals. After obtaining the feature information from hybrid feature extraction, the classification of normality and abnormality of lower limb is recognized by employing KNN classifier.

This paper is composed as follows. In Section II, a survey of several recent papers on EMG related strategies is carried out. In section III, hybrid feature extraction method is presented with multi objective classification method using KNN classifier. In Section IV experimental analysis is done for proposed and existing works. The conclusion is made in Section V.

## 2. Literature review

Several research techniques are suggested by researchers in EMG. A brief evaluation of some essential contributions to the existing literatures presented in this section.

F. Panzica, L. Canafoglia, and S. Franceschetti, [11] presented a study regarding estimation of Generalized Partial Directed Coherence (GPDC) in detecting myoclonus-related Electroencephalogram (EEG)–EMG connectivity pattern and the information flow between sensorimotor cortex and muscles in patients with typical cortical myoclonus due to Unverricht–Lundborg disease. In this literature, author analysed the EEG and EMG signals recorded during simple voluntary motor activities using GPDC, a frequency domain linear index of connectivity estimated from a multivariate autoregressive model. The proposed results clearly indicate the recruitment of extensive cortical network in afferent and efferent EEG–EMG relationships. This proposed technique was only suitable for uniform pattern datasets not for all non-uniform pattern datasets.

T. Hashimoto, T. Iwahashi, W. Ishii, K. Yamamoto, and S.I. Ikeda, [12] evaluated a patient's sporadic Creutzfeldt–Jakob Disease (CJD) who showed dystonia, periodic myoclonus, and Periodic Sharp Wave Complexes (PSWCs) on EEG. The EEG–EMG polygraphic study revealed that dystonia appeared without relation to periodic myoclonus and PSWCs and that dystonia EMGs were strongly suppressed after periodic myoclonus EMGs. These findings suggest that dystonia has a pathogenesis different from the periodic myoclonus and PSWCs, but dystonia and periodic myoclonus may be generated through the sensorimotor cortex in CJD. While performing with more number of disease the complexity of classification was increased.

J. Hu, C.S. Wang, M. Wu, Y.X. Du, Y. He, and J. She, [13] presented a new approach for removing electrooculogram (EOG) and EMG artifacts from EEG. Proposed approach contains a combination of Adaptive Neural Fuzzy Inference System (ANFIS) and Functional Link Neural Network (FLNN) to construct a filter for enhancing the nonlinear approximation ability of the method. The proposed filtering algorithm adjusts the parameters of the fuzzy inference and neural network. The experimental outcome confirmed that the proposed methodology was more significant than existing approaches by means of error rate. In a few cases, the training data were dependent evaluation or manual adjustment that needs to be automated.

N. Miljković, N. Popović, O. Djordjević, L. Konstantinović, and T.B. Šekara, [14] proposed a new methodology for automatic artifact cancellation in EMG signal surface by applying fractional order calculus and nonlinear median filter. The proposed methodology was compared with the linear moving average filter, with and without prior application of fractional order calculus. For an appropriate quantitative filtering evaluation, the synthetic Electrocardiograph (ECG) signal and analogous semi-synthetic datasets were generated. The presented result suggested that the proposed automatic artifact cancellation methodology significantly removes the ECG artifacts from EMG signal for enveloping record in trunk muscles. The proposed filtering methodology will work only for limited number of EMG channels.

S. Singh, G. Shukla, V. Goyal, A.K. Srivastava, M.B. Singh, D. Vibha, and M. Behari, [15] investigated the role of sleep and its stages on the localizing value of video EEG in the evaluation of refractory focal seizures. Localization of video EEG for each seizure was made based on clinical, ictal and interictal data. Seizure localization in each patient was assessed for concordance with MRI and other imaging data (SPECT, PET) for both wake and sleep seizures. Interictal discharges in sleep and wake were similarly compared for concordance with imaging data. Extensive experiments were conducted and the efficiency of the proposed method was verified. The

major drawback of developed methodology was energy leakage, which highly affects the detection rate.

To overcome the above mentioned drawbacks, hybrid feature extraction with multi objective classification method (KNN) is implemented for enhancing the recognition rate of normal and abnormal prediction of knee movement.

## 3. Proposed methodology

In the proposed method, the knee movement for the normal and abnormal persons is detected from the EMG signal and is divided into four major steps: signal pre-processing, transformation, hybrid feature extraction and classification. A general block diagram of the proposed method is shown in the Fig. 1.

### 3.1 Database description

An acquisition of EMG signal helps to detect skeletal related muscular information. In this scenario, EMG-Lower Limb dataset is taken for identifying normal and abnormal activities of knee movement. The acquired dataset consists of 22 male subjects,
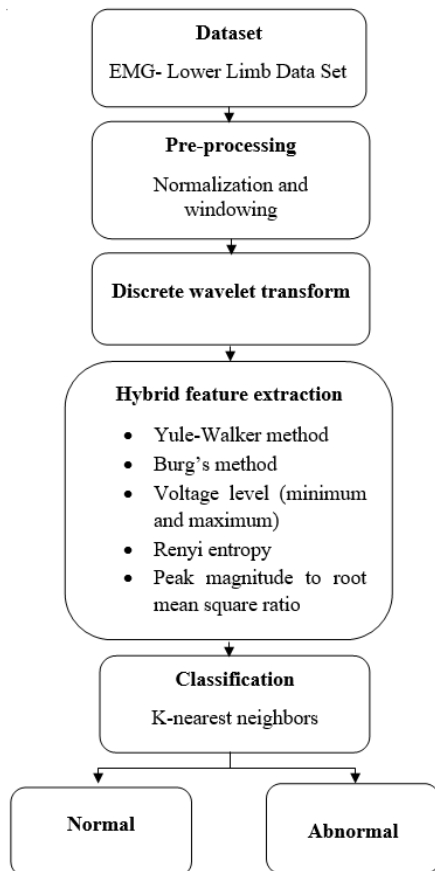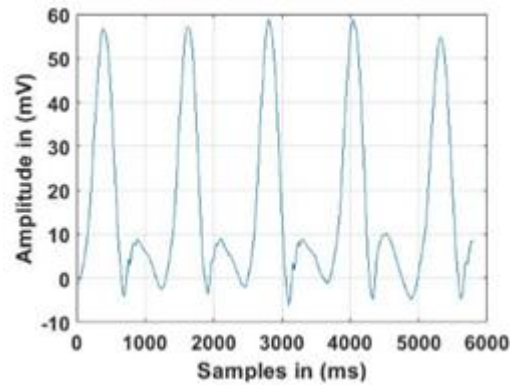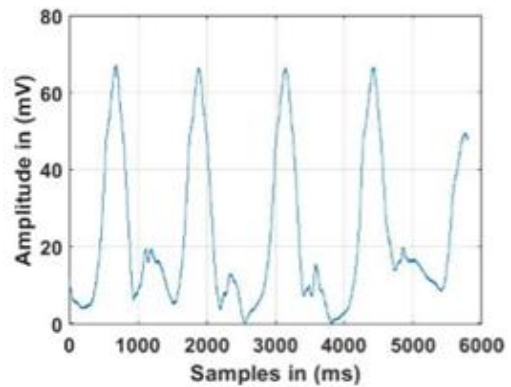


Figure.2 Normal EMG signal



Figure.3 Abnormal EMG signal

from that 11 male subjects are normal and the remaining 11 male subjects are with knee pathology. Each subject undergoes three different shots such as one gait, one standing and one sitting. The acquisition procedure was evaluated with four electrodes in five channels. Each channel corresponds to the electrode attached to a muscle, channel 1-recto femoral, channel 2-femoral biceps, channel3-vastusmedialis, channel 4-semitendinosus and channel 5-flexion at the knee. Here, we have mainly concentrated on channel 5- flexion at the knee, because it contains both the leg muscle movement and knee joint movement. By analysing these movements, we can easily identify the normal and abnormal activities of lower limb. The sample normal and abnormal waveforms of EMG-Lower Limb signals are denoted in the Fig. 2 and 3.

### 3.2 Pre-processing

After the acquisition of EMG-Lower Limb dataset, an important step in the EMG signal processing is pre-processing of acquired data. Pre-processing methods helps to remove the unwanted artifacts from the signal and also to improve the signal to noise ratio. The pre-processing block aids in improving the performance of the system by
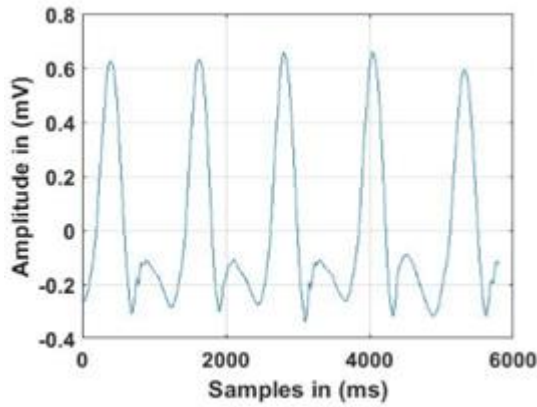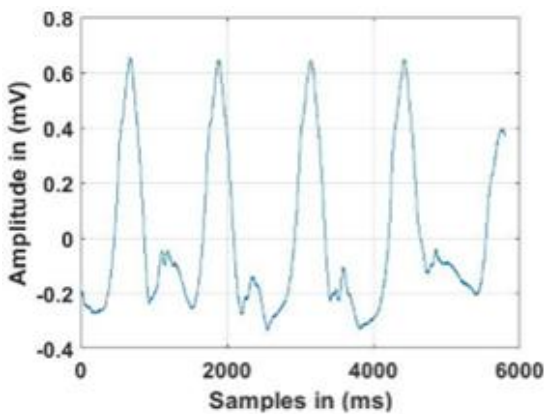


Figure.1 General block diagram of proposed methodology

Figure.4 (a) Pre-processed normal EMG signal


Figure.5 Pre-processed abnormal EMG signal


Figure.6 Windowed normal EMG signal


Figure.7 Windowed abnormal EMG signal

EMG signal. In windowing methodology, we extract the features of R peak location as the primary peaks by moving some samples to left side and right side of the signal. The normal and abnormal EMG signals of windowing technique are represented in the Fig. 6 and 7.

### 3.3 Discrete wavelet transform

The respective pre-processed EMG signal is used for transformation by employing DWT. In signal processing, DWT delivers superior time resolution and frequency resolution in EMG signal, because of its time and frequency localization ability. Also, DWT reveals the local characteristics of the input signal and helps to reduce the feature degradation. In this scenario, an improved low-frequency and high frequency information are achieved by employing short and long time windows. Also, it splits the input 60Hz frequency into five sub-bands with the range of 0-4Hz, 4-8 Hz, 8-15 Hz, 15-30 Hz and 30-60 Hz, respectively. Due to this, DWT is appropriate for investigating the non-stationary signals. General equation of DWT is specified in the Eq. (1).

$$DWT(j,k) = \frac{1}{\sqrt{|2^j|}} \int_{-\infty}^{\infty} x(N)\mu\left(\frac{N-2^jK}{2^j}\right) dN \quad (1)$$

Where, $\mu$ is denoted as the wavelet function, $x(N)$ is denoted as real valued wavelet and $2^j$ and $2^jK$ are represented as the scaling shifting parameters.

### 3.4 Hybrid feature extraction

After performing DWT, the hybrid feature extraction is applied on the five sub-bands of DWT for extracting the feature information. Whereas, the hybrid feature extraction includes yule-walker approach, burg's method, voltage level (minimum and maximum), Renyi entropy, and PMRS. In this research, the hybrid feature extraction obtains
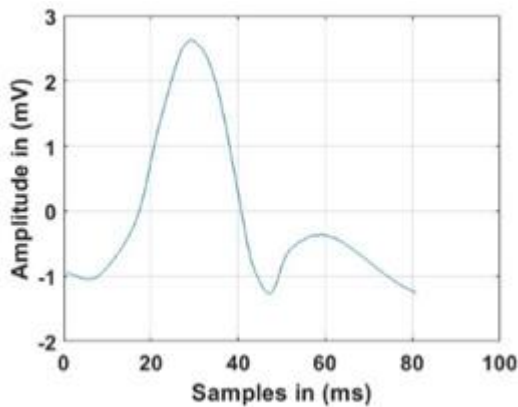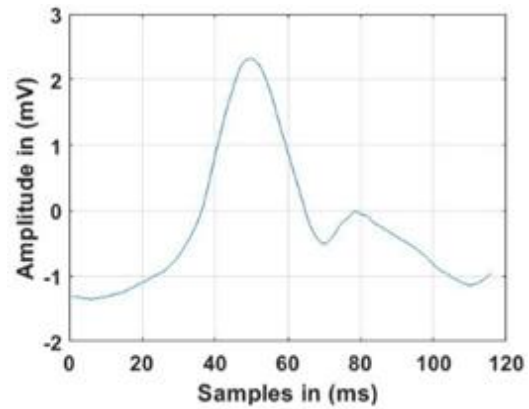
separating the noise from the actual signal. In this experimental analysis normalization procedure is undertaken for pre-processing the EMG signal. The normalization methodology sets the baseline to zero and the maximum amplitude at +1 or -1, which helps to eliminate the unwanted peaks or artifacts of the signals. The pre-processed normal and abnormal waveforms of the EMG signals are represented in the Figs. 4 and 5.

Further, to improve the accuracy of recognition and classification, windowing technique is applied to

optimal feature subsets from the EMG-Lower Limb dataset by the rejection of redundant and irrelevant features. A brief description about hybrid feature extraction is describe below.

### 3.4.1. Autoregressive features

Autoregressive methods estimate the Power Spectrum Density (PSD) of the signal using a parametric approach. The autoregressive model is representation of a type of random process, it is used to describe the time varying processes in nature. The autoregressive model specifies that the output variable depends linearly on its own previous values and on a stochastic term (an imperfectly predictable term); thus the model is in the form of a stochastic difference equation. Estimation of PSD is achieved by calculating the coefficients, which is the parameters of linear system under consideration. Two methods are used to estimate autoregressive models are briefly described below.

### 3.4.1.1. Yule-Walker method

In Yule-Walker method autoregressive parameters or coefficients are estimated by exploiting the resulting biased approximate of the autocorrelation data function [16]. This is done by subsequently finding the minimization of the least squares of the forward prediction error calculation as given in the Eq. (2).

$$\begin{bmatrix} r(0)_{xx} & \cdots & r(-p+1)_{xx} \\ \vdots & \ddots & \vdots \\ r(p-1)_{xx} & \cdots & r(0)_{xx} \end{bmatrix} \times \begin{bmatrix} a(1) \\ \vdots \\ a(p) \end{bmatrix} \quad (2)$$

Where $r_{xx}$ is defined by using the Eq. (3).

$$r_{xx}(m) = \frac{1}{N}\sum_{N=0}^{N-m-1} x^*(n)x(n+m), \ m \geq 0 \quad (3)$$

Calculating the above set of $(p + 1)$ linear equations, the auto-regressive coefficients are obtained in the Eq. (4).

$$P_{xx}{}^{BU} = \frac{\sigma_{wp}{}^2}{\left|1+\sum_{k=1}^{P}\hat{a}_p(k)e^{-j2\pi fk}\right|^2} \quad (4)$$

While, $\hat{\sigma}wp$ gives the approximated lowest mean square error of the $p$th-order predictor given as Eq. (5).

$$\sigma^2{}_{wp} = E^f{}_p = r_{xx}(0)\coprod_{k=1}^{P}[1 - |a_k(k)|^2] \quad (5)$$

### 3.4.1.2. Burg's method

Burg's method estimates the reflection coefficient directly without the need of autocorrelation function. This method has the following strength: Burg's method can estimate PSD's data records to look exactly like the original data value. It can yield intimately packed sinusoids in signals once it contains minimal level of noise. The difference between method of Yule-Walker and Burg's method is in the way of calculating the PSD [17]. For Burg's method, the PSD is estimated by using the Eq. (6),

$$P^{BU}{}_{xx}(f) = \frac{\widehat{E_P}}{\left|1+\sum_{k=1}^{P}\widehat{a_P}(k)e^{-j2\pi fk}\right|^2} \quad (6)$$

Where, $P$ determines the total error of least squares. Parametric methods like autoregressive one reduce the spectral leakage issues and yield better frequency resolution. The primary advantages of the Burg method are resolving closely spaced sinusoids in signals with low noise levels, and estimating short data records, in which case the autoregressive power spectral density estimates are very close to the true values. In addition, the Burg method ensures a stable autoregressive model and is computationally efficient.

### 3.4.2. Renyi entropy

Renyi entropy is a statistical function to measure the diversity and randomness of the discrete signal distribution and to estimate the uncertainty of the discrete signal. The generalized entropy function for discrete variable $X$ is calculated in the Eq. (7),

$$H_\alpha(X) = \frac{1}{1-\alpha}log(\sum_{i=1}^{n} p_i{}^\alpha) \quad (7)$$

Where, $p_i$ is the probability of the discrete signal variables. The order of Renyi entropy is alpha, that has the constraint of $\alpha > 0$ and $\alpha \neq 1$. In probability density function, the variable $X$ is partitioned into $k$ bins of equal width. The width of a bin $h$, is determined based on the range of $X$, where $h = (x_{max} - x_{min})/k$. The resulting formula of Renyi entropy is determined by the Eq. (8).

$$H_\alpha(X) = \frac{1}{1-\alpha}log\sum_{j-1}^{k}(\frac{v_j}{h})^\alpha \quad (8)$$

Here, the data points are dropping into the $j^{th}$ partition as $v_j$. $k$ is the number of bins and $a$ is the parameter that are varied.

### 3.4.3. Peak-magnitude to root mean square ratio and min-max voltage feature extraction

Peak-Magnitude to Root Mean Square Ratio (PMRS) is utilized to determine the positive peak and negative peak values of the single transition waveform or the single pulse waveform. The minimum peak value is represented as the low or first state level and the maximum peak value is stated as the high or second state level. The mathematical expression of PMRS is described in the Eq. (9),

$$PMRS = \frac{\|X\|_\infty}{\sqrt{\frac{1}{N}\sum_{n=1}^{N}|X_n|^2}} \qquad (9)$$

Where $X$ is represented as real or complex valued input vector, $N$ is denoted as real valued wavelet and $n$ is denoted as the number of input samples. This algorithm is suited for analysing the waveforms with state levels of negligible or relatively short duration. In addition, the maximum and minimum voltage features are extracted in EMG signal. EMG signals provide a lot of information based on voltages. The different voltages provide different kinds of knee movement information. After the feature extraction, the signals go through the classification stage where the KNN classifier is used and described in the below section.

## 3.5 Classification

After hybrid feature extraction, the classification is performed on the extracted EMG data. Classification is defined as a boundary between the classes in order to label the classes based on their measured features. In this scenario, KNN classifier is taken for classifying the normal and abnormal activities of the knee movements. The goal of using KNN classifier for pre-predicting the knee dystonia diseases is, if there is no prior knowledge about the distribution of the data, the KNN method should be one of the first choices for classification.

### 3.5.1  K-nearest neighbor

KNN is a supervised learning classification algorithm and also one of the most widely used non-parametric pattern classification method. KNN is a powerful and non-parametric classification system which bypasses the problem of probability densities completely. The KNN rule classifies $x$ by assigning the label frequently in $K$ nearest samples. Then a decision is made by examining the labels on the K-nearest neighbors and taking a vote. KNN classification was developed from the need to perform discriminant analysis when reliable parametric estimates of probability densities are unknown or difficult to determine.

Nowadays, it is the most used classification algorithm. It has less usability and laborious when the training dataset is large. This algorithm operation is based on comparing a given new record with training records and finding training records that are similar to it. It searches the space for the $k$ training records that are nearest to the new record as the new record neighbors. In this algorithm nearest is defined in terms of the distance metric such as Euclidean distance. Euclidean distance between two records (or two points in n-dimensional space) is defined in the Eq. (10).

$$\mathrm{X}_1 = (X_{11}, X_{12}, \ldots\ldots, X_{1n}), \mathrm{X}_2 = (X_{21}, X_{22}, \ldots\ldots, X_{2n}),$$

$$dist(x_1, x_2) = \sqrt{\sum_{i=1}^{n}(x_{1i} - x_{2i})^2} \qquad (10)$$

Where, $x_1$ and $x_2$ are two records with $n$ attributes. This formula measures the distance between $x_1$ and $x_2$ based on the difference between the corresponding values of the attribute in record of $x_1$ and $x_2$.

## 4.   Experimental result

In this scenario, for experimental simulation, MATLAB (version 2017a) was employed on PC with 3.2 GHz with i5 processor. In order to estimate the efficiency of proposed algorithm, the performance of proposed method was compared with Linear discriminant analysis (LDA) [18] and Support vector regression [19] on the reputed database EMG-Lower Limb dataset. The performance of the proposed method was compared in terms of accuracy, precision, recall, sensitivity, specificity and E-rate.

### 4.1 Performance evaluation

The relationship between the input and output variables of a system is understood by employing the suitable performance metrics like sensitivity and specificity. The general formula for calculating the sensitivity and specificity of normal and abnormal activities of knee movement detection rate are given in the Eqs. (11) and (12).

$$Sensitivity = \frac{TP}{TP+FN} \times 100 \qquad (11)$$

$$Specificity = \frac{TN}{TN+FP} \times 100 \qquad (12)$$

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Where, $TP$ is represented as true positive, $FP$ is denoted as false positive, $TN$ is represented as true negative and $FN$ is stated as false negative.

In addition, accuracy, precision and recall are the suitable evaluation metrics for finding the effectiveness of normal and abnormal activities of knee movement detection. Precision and recall are the measure of statistical variability and a description of random errors. The general formulas of accuracy, precision and recall for determining normal and abnormal activities of knee movement detection are given in the Eqs. (13), (14) and (15), respectively.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \times 100 \qquad (13)$$

$$Precision = \frac{TP}{TP+FP} \qquad (14)$$

$$Recall = \frac{TP}{TP+FN} \qquad (15)$$

E-rate is the measure of accuracy test, which is the ratio of incorrectly received signal divided by the total number of received signals. The general formula for E-rate measure is denoted in the Eq. (16).

$$E - rate = \frac{FP+FN}{TP+TN+FP+FN} \qquad (16)$$

## 4.2 Quantitative analysis using EMG-Lower limb dataset

In this experimental analysis, for comparing the performance evaluation of hybrid feature extraction and an individual feature, two different combinations of testing and training percentage are considered such as 40% training and 60% testing, and 80% training and 20% testing of collected data using KNN classifier. In Table 1, for 40% training and 60% testing of collected data, accuracy of the hybrid features achieves 92% and the individual features (PMRS, burg, yule, renyi, min, and max) attains 45.57%, 65%, 81.14%, 91.43%, 43.57% and 50% of accuracy.

Inspecting the Table 1, the hybrid features outperforms with higher sensitivity, specificity, precision, recall and E-rate value of 97.43%, 86.57%, 0.899, 0.977 and 0.08 compared to the individual features: PMRS, burg, yule, renyi, min, and max. The individual features achieve minimum sensitivity, specificity, precision, recall and E-rate value, compared to the hybrid feature extraction. The accuracy, sensitivity, specificity, precision, recall and E-rate comparison of hybrid and individual feature extraction using 40% training and 60% testing is graphically denoted in the Figs. 8 and 9.

Table 1. Performance evaluation using 40% training and 60% testing

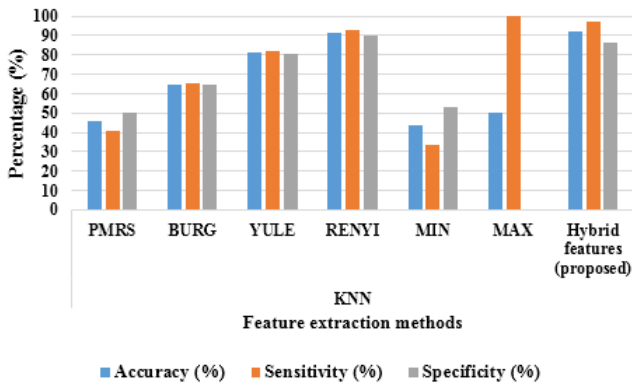| Classifier | Features | Accuracy (%) | Sensitivity (%) | Specificity (%) | Precision | Recall | E-rate |
|---|---|---|---|---|---|---|---|
| K-NN | PMRS | 45.57 | 40.86 | 50.29 | 0.439 | 0.466 | 0.544 |
| | Burg | 65 | 65.14 | 64.86 | 0.680 | 0.647 | 0.35 |
| | Yule | 81.14 | 82 | 80.29 | 0.832 | 0.832 | 0.188 |
| | Renyi | 91.43 | 92.86 | 90 | 0.923 | 0.938 | 0.0857 |
| | Min | 43.57 | 33.71 | 53.43 | 0.419 | 0.436 | 0.564 |
| | Max | 50 | 100 | 0 | 0.5 | 0 | 0.5 |
| | Hybrid features (proposed) | **92** | **97.43** | **86.57** | **0.899** | **0.977** | **0.08** |

Figure.8 Accuracy, sensitivity and specificity comparison of hybrid and individual feature extraction using 40% training and 60% testing
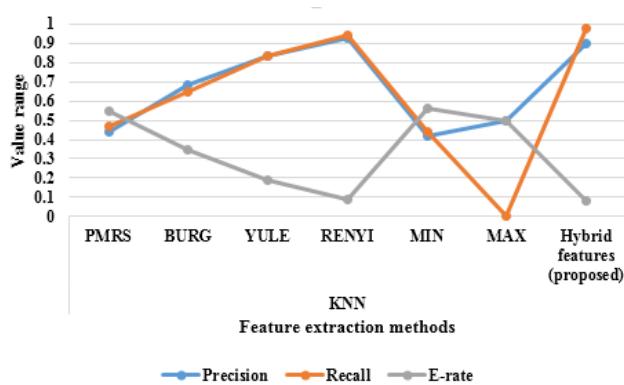


Figure.9 Precision, recall, E-rate comparison of hybrid and individual feature extraction using 40% training and 60% testing

In Table 2, accuracy of the hybrid feature extraction achieves 93.5% and the individual features (PMRS, burg, yule, renyi, min, and max) delivers 34.5%, 65%, 76.5%, 93%, 44.5% and 50% of accuracy. The proposed system improves the accuracy in knee movement detection up to 50 % compared to the individual features. Similarly, sensitivity and specificity of the hybrid feature extraction achieves better result compared to the individual features. Graphically, it is denoted in the Fig. 10.

Likewise, precision of the proposed hybrid feature extraction achieves 0.9167 and the individual features (PMRS, burg, yule, renyi, min, and max) delivers 0.24, 0.68, 0.78, 0.96, 0.4667 and 0.5 of precision. Correspondingly, recall and E-rate of the proposed system delivers better outcome compared to the individual features in KNN classifier. The table 2 confirms that the proposed methodology performs very effectively compared to the individual features in EMG-Lower Limb dataset. The precision, recall and E-rate comparison of proposed and existing methods using 80% training and 20% testing is shown in the Fig. 11.

Table 2. Performance evaluation using 80% training and 20% testing

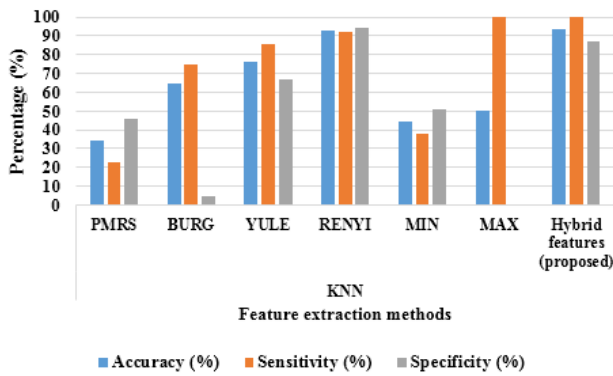| Classifiers | Features | Accuracy (%) | Sensitivity (%) | Specificity (%) | Precision | Recall | E-rate |
|---|---|---|---|---|---|---|---|
| K-NN | PMRS | 34.5 | 23 | 46 | 0.24 | 0.33 | 0.65 |
| | BURG | 65 | 75 | 5 | 0.68 | 0.633 | 0.35 |
| | YULE | 76.5 | 86 | 67 | 0.78 | 0.767 | 0.235 |
| | RENYI | 93 | 92 | 94 | 0.96 | 0.947 | 0.07 |
| | MIN | 44.5 | 38 | 51 | 0.4667 | 0.40 | 0.550 |
| | MAX | 50 | 100 | 0 | 0.5 | 0 | 0.5 |
| | **PROPOSED** | **93.5** | **100** | **87** | **0.9167** | **0.98** | **0.065** |

Figure.10 Accuracy, sensitivity and specificity comparison of hybrid and individual feature extraction using 80% training and 20% testing
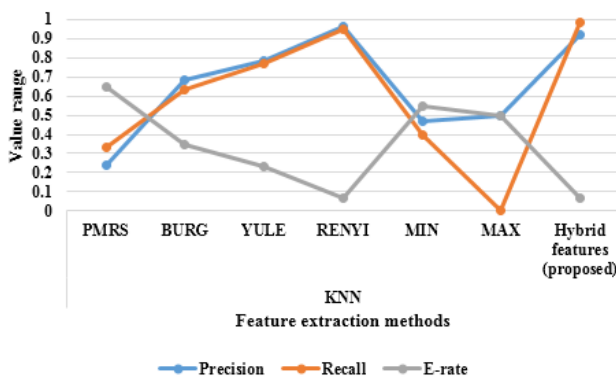


Figure.11 Precision, recall, E-rate comparison of hybrid and individual feature extraction using 80% training and 20% testing

Tables 1 and 2 clearly shows that the proposed approach improves the prediction accuracy in knee movement detection upto 7-40% compared to the individual features. In this research, the hybrid feature extraction determines the linear and non-linear characteristics of the data and preserves quantitative relationships between the low level and high level features. The evaluation metrics confirms that the proposed system performs significantly in knee movement detection compared to individual features in terms of accuracy, precision, recall, sensitivity, specificity and E-rate.

Fig. 12 represents the performance evaluation of proposed method for six different performance metrics. In 40th iteration, the proposed method almost achieved 100% of accuracy, sensitivity, specificity, precision, recall and with zero error rate. After 40th iteration, the dissimilar patterns of EMG signals are significantly learnt by the KNN classifier with the maximum point and the experimental outcome of the proposed method is saturated after the 40th iteration.
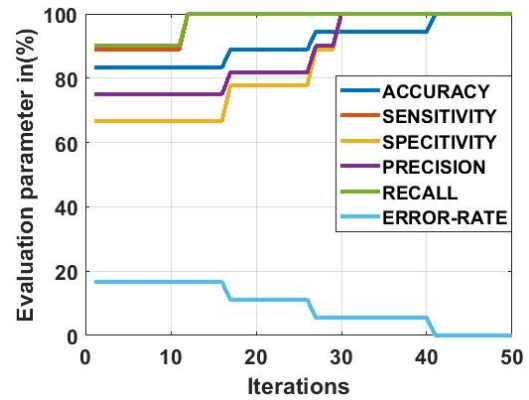


Figure.12 Iteration based performance evaluation of proposed approach

Table 3. Comparative analysis

| References | Dataset | Classification approach | Accuracy (%) |
|---|---|---|---|
| C.D. Joshi, U. Lahiri, and N.V. Thakor, [18] | EMG-Lower Limb dataset | LDA | 92.715 |
| P. Li, X. Zhu, S.W. Su, Q. Guo, P. Xu, and D. Yao, [19] | EMG-Lower Limb dataset | SVR | 91.85 |
| Proposed | EMG-Lower Limb dataset | K-NN | 93.5 |

## 4.3 Comparative analysis

Table 3 represents the comparative study of existing and proposed work performance. C.D. Joshi, U. Lahiri, and N.V. Thakor, [18] proposed Bayesian Information Criteria (BIC) with some standard feature extraction methods (time domain features, time frequency domain features, frequency domain features and auto-regression co-efficient) and linear discriminant analysis classification system for classifying different knee pattern recognition. The developed methodology achieved 92.715 % of classification accuracy.

In addition, Y. Zhang, P. Li, X. Zhu, S.W. Su, Q. Guo, P. Xu, and D. Yao, [19] developed an effective system for knee pattern identification. In first phase, a combination of both time and frequency domain features were utilized to extract the features from EMG-Lower Limb dataset. Then, five-level wavelet decomposition and support vector regression classifier was used to classify the different knee patterns. The experimental results demonstrated that

the developed methodology achieved 91.85% of classification accuracy. Whereas, the proposed work achieves 93.5% of accuracy which is higher than the existing works.

## 4.4 Contribution of the research

As discussed in the proposed approach, hybrid feature extraction is a part of knee movement detection in this paper. The individual features show limited accuracy in knee movement detection compared to hybrid features. Whereas, the hybrid features improved accuracy in knee movement detection up to 7-40% compared to individual features. The effect of hybrid feature combination is shown in the Tables 1 and 2. The proposed classification approach achieves better classification rate compared to the existing classifiers in terms of accuracy, precision, recall, sensitivity, specificity and E-rate. The proposed approach has numerous advantages; assists the physicians during surgery, cost efficient compared to the existing machine learning approaches and earlier detection of the diseases.

## 5. Conclusion

An EMG signal based knee dystonia disease prediction is one of the most significant research tasks in computer-aided diagnosis. The objective of this paper is to develop a proper feature for classifying the normal and abnormal action of knee movements for pre-predicting the knee dystonia diseases using EMG-Lower Limb dataset. In this scenario, hybrid feature extraction (yule-walker, burg's, voltage level (minimum and maximum), Renyi entropy, and PMRS) is employed for attaining optimal feature subsets and the irrelevant features are rejected. Using these feature information's, the normal and abnormal action of knee movements are classified using KNN classifier. Compared to other existing methods in knee movement prediction, the proposed methodology delivered an effective performance by means of accuracy and shows 0.785-1.65% of improvement in classification accuracy. In the future work, for improving the classification rate of knee movement action, we will combine appropriate feature extraction approaches with multi class learning classification methodology.

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